

# Differential Equations

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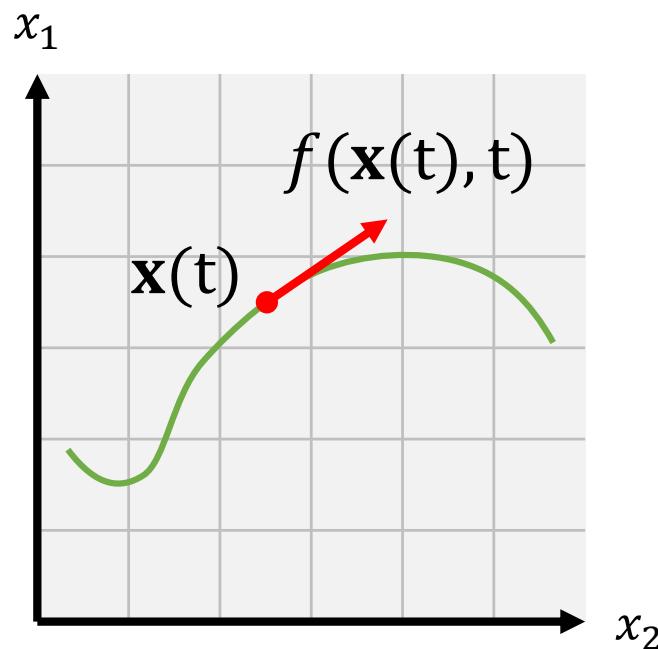
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*Physically Based Modeling* (SIGGRAPH 2001 course) by Andrew Witkin

# Differential Equations

- It describes the relation between an unknown function and its (first, second, partial, etc) derivatives
- Many natural phenomena can be explained by using differential equations
  - Newton's equation (motions of macroscopic objects)
  - Diffusion equation (heat transfer)
  - Maxwell equation (electromagnetism)
  - Navier-Stokes equation (motions of fluids)

# A Canonical Differential Equation

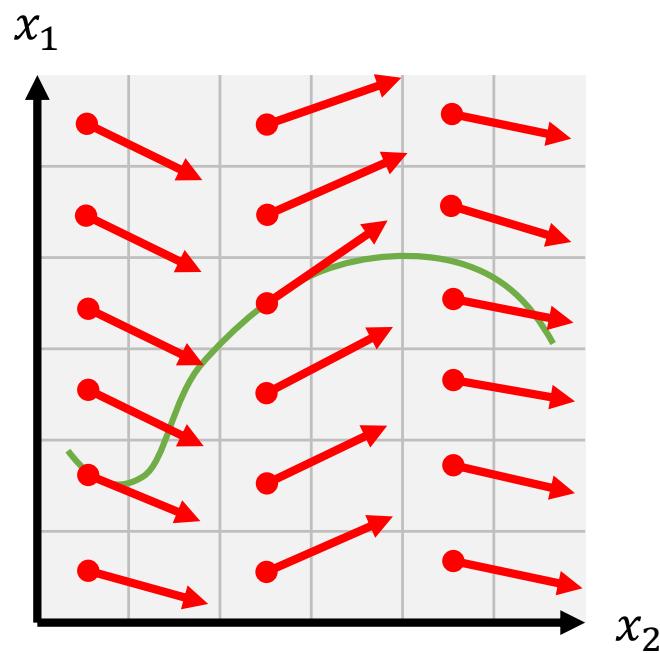


$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), t)$$

$\mathbf{x}(t)$ : a state of the system

$f(\mathbf{x}(t), t)$ : the time derivative of  $\mathbf{x}(t)$

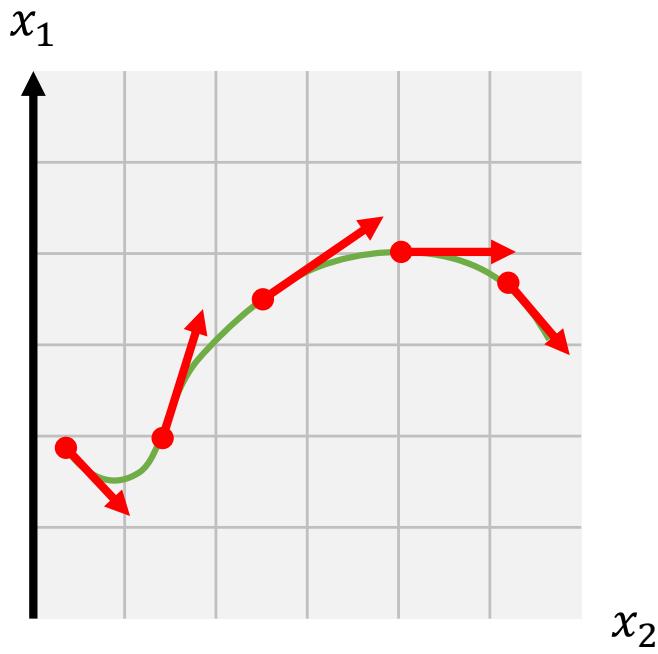
# Vector Field



$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), t)$$

- The differential equation defines a vector field regarding the velocity
- If  $\mathbf{x}(t)$  is a location of moving point  $\mathbf{p}$  at time  $t$ , the equation tells us that the point should have the same velocity to  $f(\mathbf{x}, t)$  given its location  $\mathbf{x}(t)$

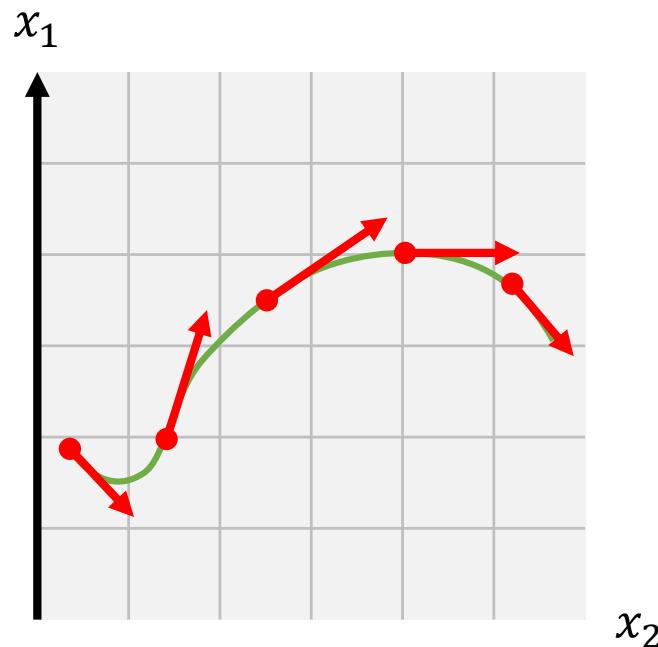
# Integral Curves



$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), t)$$

- We can think  $f$  as driving  $\mathbf{p}$  from point to point, like an ocean current
- Once a point  $\mathbf{p}$  is dropped at the location  $\mathbf{x}$  at time  $t$ , all future motion is fully determined by  $f$
- The trajectory swept out by  $\mathbf{p}$  through  $f$  forms an **integral curve** of the vector field

# Initial Value Problems

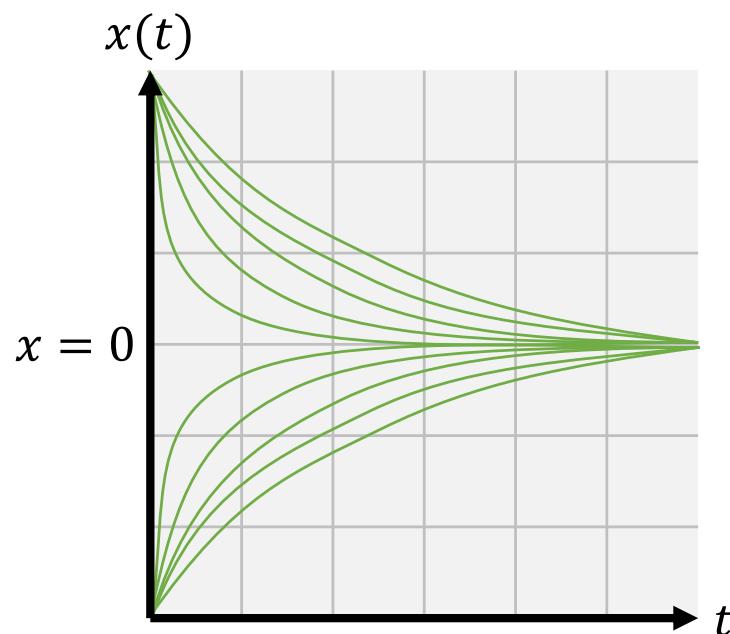


$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), t)$$

- Given the starting point, find the integral curve
- Note that ***when to start*** in addition to ***where to start*** could also affects the results if  $f$  depends directly on time  $t$

# Analytical Methods

- Ways to get analytical solutions
  - Substitution
  - Series expansion
  - Laplace transform



$$\dot{x}(t) = -kx(t)$$

$$\therefore x(t) = e^{-kx(t)}$$

# Numerical Methods

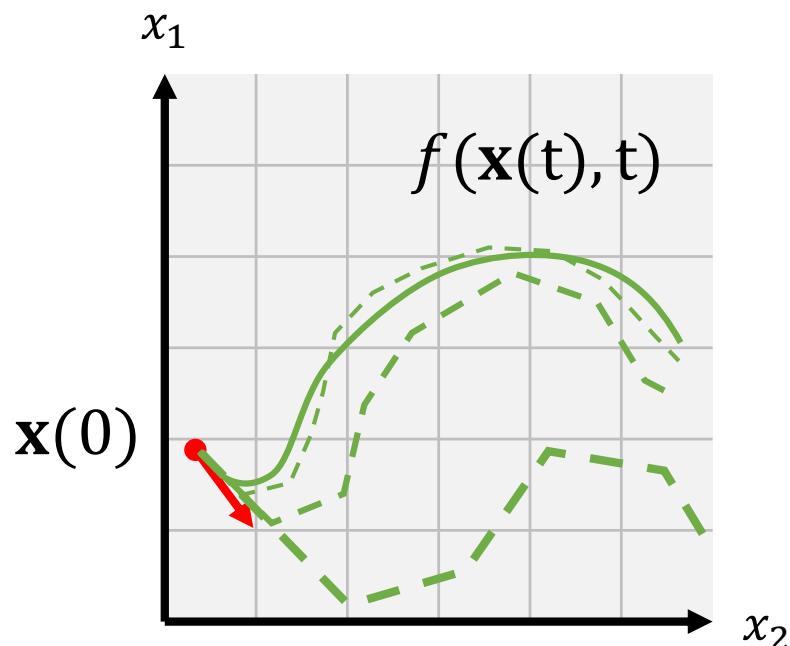
- As  $f$  gets complex, it gets harder to find analytical solutions
- Instead, we can use numerical methods to compute approximate integral curves
- The idea is to compute the change of state  $\Delta x$  over the fixed time interval  $h = \Delta t$  by using  $\dot{x} = f$  (i.e. instantaneous velocity)

# Euler's Method

$$\mathbf{x}(t + h) = \mathbf{x}(t) + \underline{h\dot{\mathbf{x}}}$$

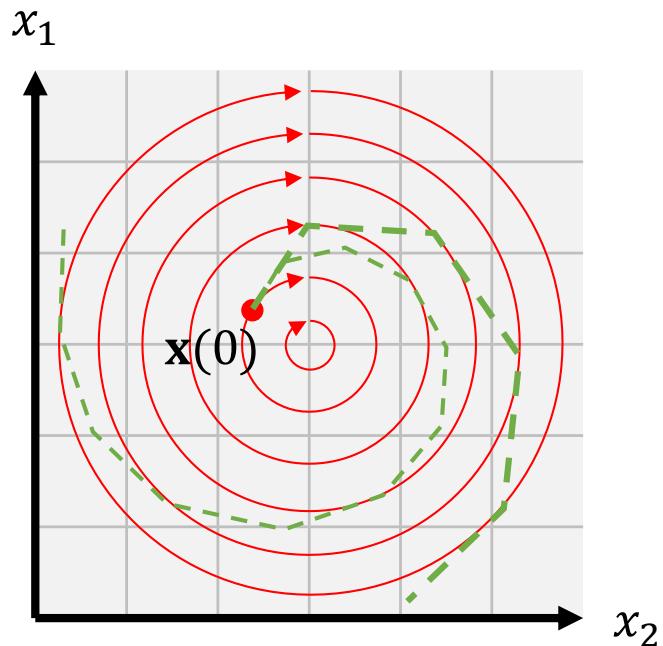
It assumes that the velocity does not change during the timestep  $h$

$$\mathbf{x}(t + h) = \mathbf{x}(t) + h f(\mathbf{x}(t), t)$$



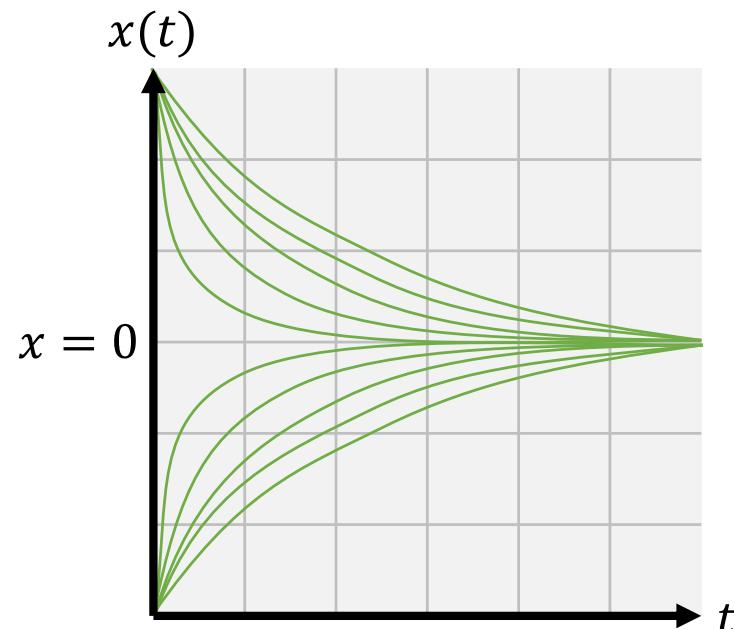
- Simplest numerical method
- Discrete time steps
- Bigger steps, bigger errors
- Smaller steps, larger computation

# Problem 1: Inaccuracy



- Suppose we have a vector field rotating around with respect to a point, where any (exact) integral curves should be concentric circles
- When using Euler's method, the radius of integral curve gets larger and larger (i.e. spiral curves) regardless of timestep size

# Problem 2: Instability



$$\dot{x}(t) = -kx(t)$$

$$x(t + h) = x(t) + h(-kx(t))$$

- When  $h > 1/k$ , we have  $|\Delta x| = |x|$ , so the solution oscillates around zero
- When  $h \geq 2/k$ , the solution does not converge
- Beyond  $h > 2/k$ , the oscillation diverges, and the system blows up

# Euler's Method: Tayler Series

$$\mathbf{x}(t_0 + h) = \mathbf{x}(t_0) + h\dot{\mathbf{x}}(t_0) + \frac{h^2}{2!}\ddot{\mathbf{x}}(t_0) + \cdots + \frac{h^n}{n!}\frac{\partial^n \mathbf{x}(t_0)}{\partial t^n}$$

Euler's method

Error occurred due to linear approximation  
 $O(h^2)$

- Suppose we take steps of size  $h/m$ , this will produces about  $(h/m)^2$  error at each timestep, and we need to take  $m$  steps more to simulate the original duration
- In total, the error is reduced ***linearly*** as we decrease the timestep

$$(h)^2 \cdot 1 = h^2 \quad \longrightarrow \quad \left(\frac{h}{m}\right)^2 \cdot m = \frac{h^2}{m}$$

# The Mid-point Method

$$\mathbf{x}(t_0 + h) = \mathbf{x}(t_0) + h\dot{\mathbf{x}}(t_0) + \frac{h^2}{2!}\ddot{\mathbf{x}}(t_0) + \dots + \frac{h^n}{n!}\frac{\partial^n \mathbf{x}(t_0)}{\partial t^n}$$

$O(h^3)$

$$\ddot{\mathbf{x}} = \frac{\partial f}{\partial \mathbf{x}} \frac{\partial \mathbf{x}}{\partial t} + \frac{\partial f}{\partial t}$$

Complicated to evaluate!

$$f(\mathbf{x}_0 + \Delta \mathbf{x}, t_0 + \Delta t) = f(\mathbf{x}_0, t_0) + \Delta \mathbf{x} \frac{\partial f}{\partial \mathbf{x}} + \Delta t \frac{\partial f}{\partial t} + \dots$$

$$f\left(\mathbf{x}_0 + \frac{h}{2}f, t_0 + \frac{h}{2}\right) = f(\mathbf{x}_0, t_0) + \frac{h}{2} \left( \frac{\partial \mathbf{x}}{\partial t} \frac{\partial f}{\partial \mathbf{x}} + \frac{\partial f}{\partial t} \right) + O(h^2)$$

$$\frac{h^2}{2}\ddot{\mathbf{x}}(t) + O(h^3) = h \left( f\left(\mathbf{x}_0 + \frac{h}{2}f, t_0 + \frac{h}{2}\right) - f(\mathbf{x}_0, t_0) \right)$$

$$\Delta \mathbf{x} = \frac{h}{2}\dot{\mathbf{x}}(t_0) = \frac{h}{2} \frac{\partial \mathbf{x}}{\partial t}$$

$$\Delta t = \frac{h}{2}$$

Rearrange &  
Multiply  $h$  both sides

# The Mid-point Method

$$\boxed{\frac{h^2}{2} \ddot{\mathbf{x}}(t) + O(h^3)} = h \left( f \left( \mathbf{x}_0 + \frac{h}{2} f, t_0 + \frac{h}{2} \right) - f(\mathbf{x}_0, t_0) \right)$$



$$\mathbf{x}(t_0 + h) = \mathbf{x}(t_0) + h\dot{\mathbf{x}}(t_0) + \boxed{\frac{h^2}{2!} \ddot{\mathbf{x}}(t_0) + \dots + \frac{h^n}{n!} \frac{\partial^n \mathbf{x}(t_0)}{\partial t^n}}$$



$$\mathbf{x}(t_0 + h) = \mathbf{x}(t_0) + h\dot{\mathbf{x}}(t_0) + h \left( f \left( \mathbf{x}_0 + \frac{h}{2} f, t_0 + \frac{h}{2} \right) - f(\mathbf{x}_0, t_0) \right) + O(h^3)$$

$$\mathbf{x}(t_0 + h) = \mathbf{x}(t_0) + h f \left( \mathbf{x}_0 + \frac{h}{2} f(\mathbf{x}_0, t_0), t_0 + \frac{h}{2} \right) + O(h^3)$$

Mid-point method

# The Mid-point Method

- The mid-point method is a 2nd-order method, (i) an euler step is computed, then (ii) the derivative is evaluated again at the step's midpoint which is used to calculate the step

$$\mathbf{x}(t_0 + h) = \mathbf{x}(t_0) + h f\left(\mathbf{x}_0 + \frac{h}{2} f(\mathbf{x}_0, t_0), t_0 + \frac{h}{2}\right)$$

- The error is reduced ***quadratically*** as we decrease the timestep

$$(h)^3 \cdot 1 = h^3 \quad \longrightarrow \quad \left(\frac{h}{m}\right)^3 \cdot m = \frac{h^3}{m^2}$$

# Higher-order Methods

- By evaluating  $f$  a few more times, we can eliminate higher and higher orders of derivatives. The most popular procedure for doing this is a method called **Runge-Kutta** of order 4 and has an error per step of  $O(h^5)$

$$k_1 = hf(\mathbf{x}_0, t_0)$$

$$k_2 = hf\left(\mathbf{x}_0 + \frac{k_1}{2}, t_0 + \frac{h}{2}\right)$$

$$k_3 = hf\left(\mathbf{x}_0 + \frac{k_2}{2}, t_0 + \frac{h}{2}\right)$$

$$k_4 = hf(\mathbf{x}_0 + k_3, t_0 + h)$$

$$\mathbf{x}(t_0 + h) = \mathbf{x}_0 + \frac{1}{6}k_1 + \frac{1}{3}k_2 + \frac{1}{3}k_3 + \frac{1}{6}k_4$$

# Adaptive Stepsizes

- If we choose a fixed stepsize, we can only proceed as fast as the worst sections of  $\mathbf{x}(t)$  will allow. By measuring an error  $e$ , we can change stepsize adaptively in runtime

$$e = |\mathbf{x}_a - \mathbf{x}_b|$$

$\mathbf{x}_a$ : an estimate by taking an Euler step of size  $h$

$\mathbf{x}_b$ : an estimate by taking an Euler step of size  $h/2$

- Suppose that we are willing to have an error of as much as  $10^{-4}$  per step, where  $\mathbf{x}_a, \mathbf{x}_b$  should differ from each other by  $O(h^2)$ 
  - If the current error is  $10^{-8} \left(\frac{10^{-4}}{10^{-8}}\right)^{1/2} h = 100h$   Can increase timestep upto 100
  - If the current error is  $10^{-3} \left(\frac{10^{-4}}{10^{-3}}\right)^{1/2} h \approx .316h$   Should decrease timestep by 0.316 at least

# Summary

- We have learned the basics of ordinary differential equations and some numerical methods for solving the equations
- In the upcoming lectures, we will use those methods to simulate many natural phenomena by integrating ODEs
- Euler's method is rarely used in real applications but it provides a foundation of numerical approaches